

High stakes Where's Waldo

Watching for nuclear weapon material

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[hebster, commons.wikipedia.org]

Credit for the worthwhile parts of this talk goes to:



Prof. Yousry Azmy
My advisor

Prof. Dan Cacuci
Sensitivities and data assimilation expert



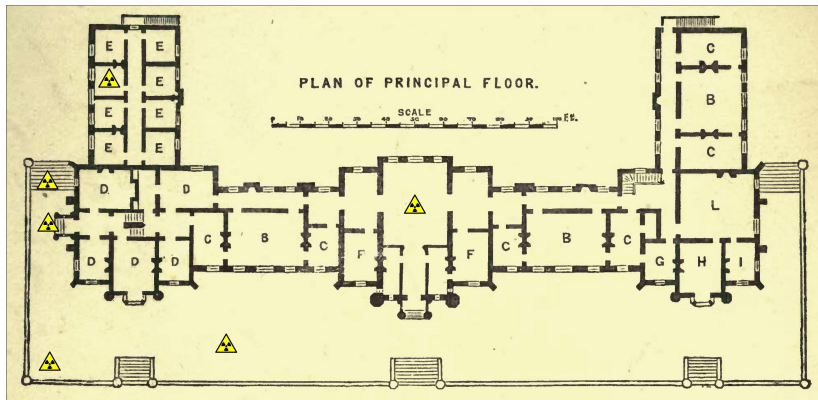
Prof. John Mattingly
Materials detection expert

The CSGF is a tremendous opportunity



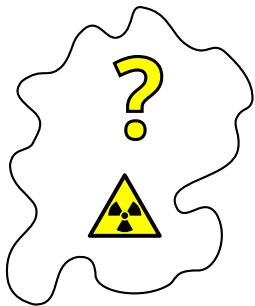
\approx TA/RA

My main thesis research is on computational methods for radiation source location

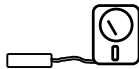


[based on an illustration by Henry Melville, 1852]

This talk focuses on the problem of estimating material quantities with remote sensing

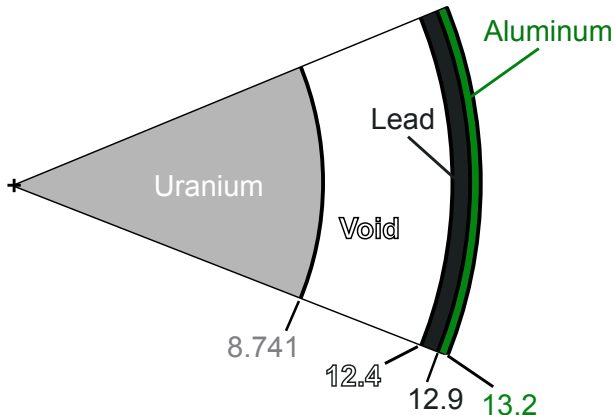


Unknown materials



Radiation detector

In practice, the materials are assumed to be a set of spherical shells



[as suggested by Favorite in 2004]

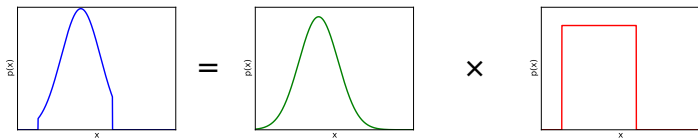
Bayesian inference is a general approach to solving inverse problems

$$p(\text{model} \mid \text{data}) \propto p(\text{data} \mid \text{model}) \cdot p(\text{model})$$

posterior

likelihood

prior



See *Inverse Problem Theory* by Albert Tarantola for more details.



We compute the first and second moments around the maximum of the posterior

$$p(\vec{z} | C) = \frac{1}{\sqrt{|2\pi C|}} \exp \left[-\frac{1}{2} Q(\vec{z}) \right]$$

where

$\vec{\alpha} \equiv$ model variables

$\vec{\alpha}^0 \equiv$ prior model values

$C_\alpha \equiv$ $\vec{\alpha}$ covariances

$\vec{r} \equiv$ measurement variables

$\vec{r}_m \equiv$ measurement data

$C_m \equiv$ \vec{r}_m covariances

$C_{\alpha r} \equiv$ $\vec{\alpha}$ -to- \vec{r}_m "covariances"

$$\vec{z} \equiv \begin{bmatrix} \vec{\alpha} - \vec{\alpha}^0 \\ \vec{r} - \vec{r}_m \end{bmatrix}$$

$$C \equiv \begin{bmatrix} C_\alpha & C_{\alpha r} \\ C_{\alpha r}^T & C_m \end{bmatrix}$$

$$Q(\vec{z}) \equiv \vec{z}^T C^{-1} \vec{z}$$

[Cacuci 2010]

Gauss-Newton optimization of $Q(\vec{z})$ searches for $\vec{\alpha}^*$ with the maximum posterior

$$\vec{\alpha}_{m+1} = \vec{\alpha}_m - \lambda_m \left(\nabla_{\alpha}^2 Q(\vec{z}_m) \right)^{-1} \vec{\nabla}_{\alpha} Q(\vec{z}_m)$$

with the linearization

$$\vec{r} = \vec{R}(\vec{\alpha}_m) + S(\vec{\alpha}_m)(\vec{\alpha} - \vec{\alpha}_m) \quad \text{where} \quad [S(\vec{\alpha})]_{i,j} = \left. \frac{\partial \vec{R}_i}{\partial \alpha_j} \right|_{\vec{\alpha}}$$

[Kelley 1999]

The thicknesses of each material are put in $\vec{\alpha}$,

$$\vec{\alpha} = \left[\log_e \frac{\Delta \rho}{\Delta \rho_0} \right]$$

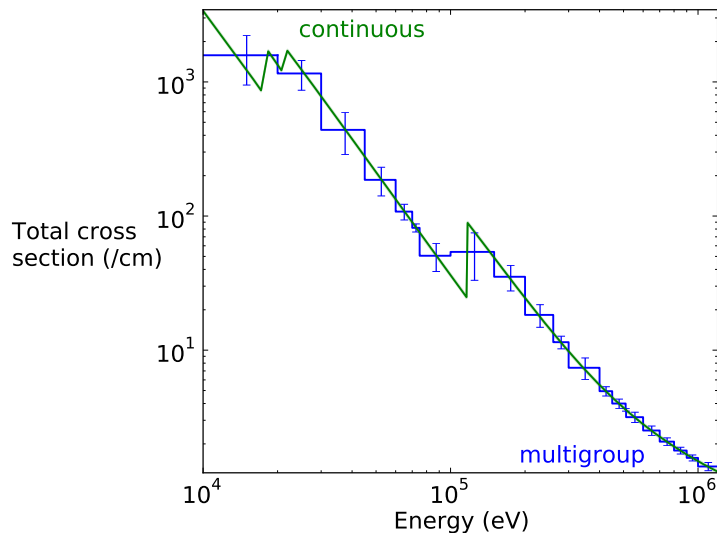
The thicknesses of each material are put in $\vec{\alpha}$, as well as uncertain material properties

$$\vec{\alpha} = \begin{bmatrix} \log_e \frac{\vec{\Delta\rho}}{\Delta\rho_0} \\ \vec{\sigma}_t \end{bmatrix}$$

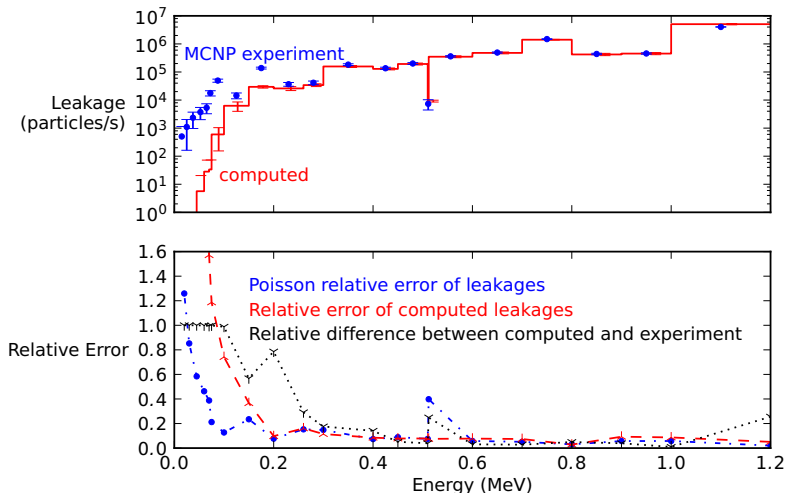
The thicknesses of each material are put in $\vec{\alpha}$, as well as uncertain material properties

$$\vec{\alpha} = \begin{bmatrix} \log_e \frac{\Delta \rho}{\Delta \rho_0} \\ \vec{\sigma}_t \end{bmatrix} \begin{array}{l} 4 \text{ components} \\ \sim 10^3 \text{ components} \end{array}$$

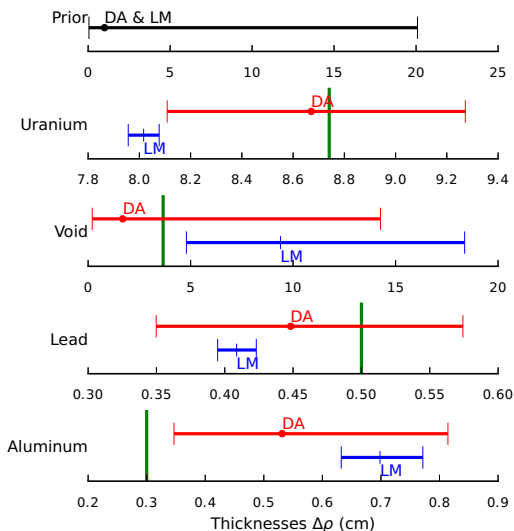
We can't know the input data $\vec{\sigma}_t$ perfectly



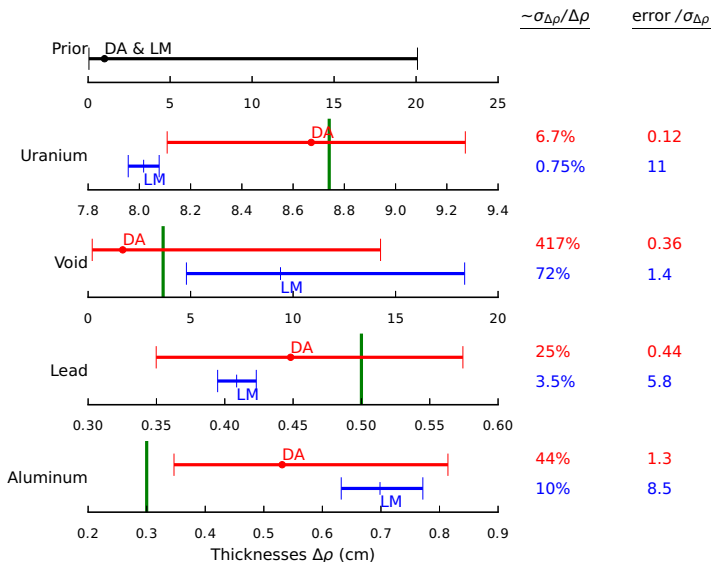
Uncertainty in the input helps to explain modeling discrepancies



Including $\bar{\sigma}_t$ uncertainties, the posterior PDF gives a reasonable estimate of the thicknesses



Including $\bar{\sigma}_t$ uncertainties, the posterior PDF gives a reasonable estimate of the thicknesses



References

- Albert Tarantola, *Inverse problem theory and methods for model parameter estimation*, SIAM 2005.
- Jeffrey Favorite, “Using the Schwinger variational functional for the solution of inverse transport problems” *Nuclear Science and Engineering* **146** 2004.
- Dan Cacuci and Mihaela Ionescu-Bujor, “Best-estimate model calibration and prediction through experimental data assimilation–I: mathematical framework” *Nuclear Science and Engineering* **165** 2010.
- CT Kelley, *Iterative Methods for Optimization*, SIAM 1999.